International Journal of Civil, Structural, Environmental and Infrastructure Engineering Research and Development (IJCSEIERD)
ISSN(P): 2249-6866; ISSN(E): 2249-7978
Vol. 5, Issue 2, Apr 2015, 25-34

LINEAR REGRESSION AND ARTIFICIAL NEURAL NETWORKS FOR MODELING COMPRESSIVE STRENGTH OF SOIL-BASED CLSMS

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ABSTRACT

This paper aims to develop predictive models for compressive strength of soil-based controlled low-strength material (CLSM) using in backfilling construction. Two mathematical methodologies were applied: multiple linear regression and artificial neural network (ANN). The data employed for analyzing was obtained from our experiment conducted in laboratory, including compressive strength and ultrasonic pulse velocity (UPV). In the mixtures, Class F fly ash was used as a part of Portland cement; fine aggregate was generated from blending surplus soil and concrete sand with a prior selected ratio (6:4). As a result, two models for strength prediction have been successfully proposed (Model-A1 and A2). In each model, four strength predicted formulas were developed; one from linear regression analysis and three from ANN-based approach (feed forward, cascade back propagation and radial basis function neural networks). Correlation analysis shows that all the proposed regression equations exhibit a well-predicted capacity for compressive strength of the CLSM.

KEYWORDS: Unconfined Compressive Strength, Ultrasonic Pulse Velocity, Prediction, Artificial Neural Network

INTRODUCTION

Nowadays, controlled low-strength material (CLSM), commonly used as granulated compacting soil, subgrades or trench fills, would be a friendly-economical material due to effective consuming a massive quantity of waste materials such as combustion fly ash, foundry sand, rubber tires, and other industrial byproducts. Self-compacting, self-leveling, low strength, as well as almost no measured settlement after hardening are remarkable characteristics of CLSM. Recent studies have reported that maximum CLSM strength of approximately up to 1.4 MPa is suitable for most of backfilling applications that re-excavation with simple tools in future is desired.(Lachemi et al., 2010; Taha et al., 2007; Wu and Tsai, 2009)The control of strength development presents challenges for mixture proportioning of CLSM. It must simultaneously satisfy the minimal strength for supporting upper structures and be limited the maximal strength for future excavation.(Alizadeh et al., 2014; Du L et al., 2002). It is recommended that depending upon availability and project requirements, any recycle materials would be acceptable in production of CLSM with prior tests it feasibility before uses. Literature reviews show that on-site residual soil after pipeline excavation could be an alternative source for fine constituent in production of soil-based CLSM, which is effectively used as backfill material around buried pipelines. (Chen and Chang, 2006; Finney et al., 2008; Howard et al., 2012) However, it is noteworthy that not all of excavated soils are considered as a source for CLSM. Previous studies have reported that combination of sand with unused soil was expected to improve the material grading.(Howard et al., 2012; Sheen et al., 2013)Due to high flow ability in nature, the CLSM strength–developing behavior would be different from normal concrete; and there has currently been a lack of

consideration on this issue. An adequate model for describing well the strength development would be helpful for engineer to understand in-depth about the soil-based CLSM.

Construction of underground infrastructures or high-rise buildings usually generates a huge amount of excavated soil.(Wu and Lee, 2011; Le, 2014) It needs to be removed, while a considerable amount of natural materials (e.g. river sand, granular soil) is likely transported to jobsite for backfills. Reusing construction wastes like on-site surplus soil would be a promising solution, oriented toward environmental-friendly policies. In this paper, a laboratory study was conducted on soil-based CLSM, in which fly ash was considered as a part of Portland cement in mixtures. In addition, based on the testing data two regressive models being different in input variables were proposed to model the compressive strength development of the proposed CLSM. For this purpose, two mathematical approaches e.g., multiple linear regression method and artificial neural network (ANN) are utilized for analyzing. Finally, performance of the developed regression formulas are compared with each other via measurement of the statistic parameters.

LABORATORY STUDIES

Materials Used and Mixture Proportions

In the experiment, materials for the CLSM mixture consist of fine aggregate, cement, fly ash, and water. Fine aggregate was formed by well blending between river sand and residual soil collected from a jobsite with a given proportion (e.g., 4:6, by weight) for improvement of grading. Visual observation and physical tests show that the residual soil is a silty-sand with liquid limit (LL) and plastic index (PI) of 16 and 3.5, respectively; it is classified as a soil of SM (silty sand), in accordance with the Unified Soil Classification System (USCS). Its fine constituent passing the No. 200 sieve (0.075 mm) was about 20%, and the fine modulus was 1.27. In addition, river sand with the fine modulus of 2.51 conforms to the ASTM C33 (ASTM:C33, 2003)of fine aggregate for concrete production. Moreover, Type I ordinary Portland cement (OPC) and Class F FA were used asa blended binder. The FA with the fineness, Blaine, of 3480 cm^2/g provided by a local Power Plant was partially substituted for OPC. Regarding mix proportion, three mixing groups corresponding to three binder contents (e.g. 80-, 100-, and 130 kg/m^3) were produced for investigation. During mix design, several water-binder ratios (*w/b*) have been selected after few trial mixes, which satisfied the CLSM flow requirement. In addition, four levels of OPC replacement with FA were launched (i.e., 0%, 15%, 30%, and 45%) each level of binder contents (OPC+FA). As a result, a series of 20 mixtures were provided for the experimental program. Table 1 summarizes material constituents for each of 20 mixtures.

Measurement of Unconfined Compressive Strength (UCS) and Ultrasonic Pulse Velocity (UPV)

UCS test were conducted on group of three 100 × 200-mm cylinders and the averaged values were obtained at various testing ages (e.g., 1-, 7-, 28-, 56-, and 91 days) conforming to the ASTM D4832.(ASTM:D4832, 2002)Table 1 reports the results of compressive strength test. It is found that the 28-day UCS of CLSM ranged from 0.21–0.47 MPa, 0.20–0.83 MPa, 0.74–1.2 MPa corresponding to binder content of 80, 100, and 130 kg/m^3, respectively. Therefore, CLSM mixtures contained 30% or less FA replacement for OPC is acceptable for the use as compacted soil, when binder content of 80–100 kg/m^3; and the 45% FA mixture had inadequate strength for the use of backfill. Moreover, all the proposed CLSM could be excavatable for maintenance owning to its 28-day strength being less than 1.4 MPa, as recommended by several researchers.(Lachemi et al., 2010; Taha et al., 2007). With respect to factors influencing compressive strength, it is revealed that mixture prepared with more binder content could be accompanied by a higher strength. Moreover, the higher either *w/b* or FA content, the lower compressive strength would be at each testing age. There was a noticeable strength loss

as the FA substitution ratio increased, especially at later ages. For instance, mixture with 100 kg/m^3 and 45% FA replacement for OPC was resulted in a drastic strength drop of beyond 60% for specimens at 7 days or later. This behavior of CLSM is found to be different from FA concrete usually made with a considerably low water-binder ratio.(Poon et al., 2000; Lam et al., 1998)

In addition, results of UPV measuring on the cylindrical specimens were tabulated in Table 1 along with the measured UCS. It was seen that the 28- and 91-day UPV were in ranges of 505–1226 m/s and 668–1240 m/s, respectively, which are several times as less as those of concrete. As expected, when FA partially substituted for OPC in mixture, a tendency of UPV reduction was observed at each testing ages and binder content levels.

Table 1: Mixture Proportion and the Testing Results for UCS (m/s) and UPV (MPa)

FA	Water-Binder Ratio	Water -Solid Ratio	1 Days		7 Days		28 Days		56 Days		91 Days	
			UPV	UCS	UPV	UCS	UPV	UCS	UPV	UCS	UPV	UCS
a. B80 (OPC+FA = 80 kg/m^3)												
0%	5.0	0.27	812	0.15	837	0.39	934	0.47	981	0.49	972	0.5
15%	5.0	0.27	797	0.14	820	0.29	900	0.36	938	0.39	924	0.39
30%	5.0	0.27	684	0.14	812	0.25	840	0.27	849	0.32	861	0.33
45%	5.0	0.27	645	0.13	704	0.19	715	0.21	763	0.28	752	0.31
b. B100 (OPC+FA = 100 kg/m^3)												
0%	3.0	0.17	784	0.21	788	0.51	805	0.83	947	0.88	1001	0.91
15%	3.0	0.17	733	0.15	773	0.4	775	0.5	833	0.66	913	0.68
30%	3.0	0.17	662	0.14	670	0.32	723	0.38	628	0.51	699	0.53
45%	3.0	0.17	644	0.13	420	0.21	505	0.25	575	0.35	668	0.38
0%	3.2	0.19	765	0.18	800	0.49	815	0.69	1080	0.86	1172	0.89
15%	3.2	0.19	720	0.13	755	0.33	798	0.39	990	0.63	1049	0.64
30%	3.2	0.19	685	0.11	700	0.26	743	0.33	930	0.56	976	0.58
45%	3.2	0.19	612	0.1	550	0.17	618	0.21	830	0.27	897	0.3
0%	3.4	0.21	705	0.13	755	0.34	828	0.52	918	0.67	981	0.68
15%	3.4	0.21	692	0.13	693	0.29	705	0.36	795	0.56	875	0.57
30%	3.4	0.21	609	0.1	665	0.25	675	0.29	805	0.47	897	0.49
45%	3.4	0.21	558	0.09	538	0.15	578	0.2	640	0.3	798	0.33
c. B130 (OPC+FA = 130 kg/m^3)												
0%	3.2	0.3	969	0.43	1164	0.96	1226	1.2	1227	1.27	1240	1.31
15%	3.2	0.3	878	0.33	1013	0.68	1112	0.87	1205	1.04	1259	1.17
30%	3.2	0.3	765	0.25	955	0.57	1155	0.78	1167	0.87	1197	0.98
45%	3.2	0.3	732	0.23	941	0.51	1081	0.74	1086	0.81	1136	0.91

IDENTIFYING COMPRESSIVE STRENGTH MODELS AND ANALYZING APPROACHES

Identification of the Strength Models

Two assumptions for modeling the compressive strength of CLSM were proposed. First, compressive strength is assumed to be a function of mixture proportions and the testing age. Accordingly, the studied CLSM mixtures consist of four material components (OPC, fly ash, aggregate, and mixing water). Hence, in this approach, there are totally five input variables, representing the mixture ingredients and the testing age of specimens in days and one output variable, reflecting the compressive strength. Second, known as non-destructive examination approach, the compressive strength can be determined by using ultrasonic pulse velocity propagating through specimens, in which the effects of several factors such as mixture contents and ages are taken into account. From the experimental program, we have built up a data set of material constituents in mixture along with their corresponding pairs of UCS and UPV values at different testing ages.

For solution of strength regression problem, it was reasonably given that the compressive strength is a dependent variable (response), whereas the others are independent variables (explanatory). In mathematical, the functional relationship between the response and explanatory variables can be expressed as the following Eqs. 1–3,(Le, 2014):

$$t = y(\mathbf{x}, \mathbf{w}) + e \tag{1}$$

For first approach (called as Model–A1, using material contents and age):

$$\mathbf{x} = (AGE, B, FA, W_s, W_b);\ t = UCS \tag{2}$$

For second approach (called Model–A2, using material contents, age, and UPV):

$$\mathbf{x} = (UPV, AGE, B, FA, W_s, W_b);\ t = UCS \tag{3}$$

where, *AGE* –age of CLSM specimens (days); *B* –binder content (kg/m^3); *FA*–percentage of fly ash substitution for cement; W_s –water-to-solid ratio; W_b –water-to-binder ratio; *UPV*–ultrasonic pulse velocity in m/s; UCS –unconfined compressive strength of CLSM in MPa; $y(\mathbf{x}, \mathbf{w})$ –regression functional on input vector $\mathbf{x}$ needed to be determined; $\mathbf{w}$ –vector of adjusted coefficients; e – noisy data.

Multiple Linear Regression (MLR)

In general, regression is known an effective statistical technique to develop an empirical correlation between a dependent variable and one or more independent variables by minimizing the norm of a residual vector. In the proposed MLR models, the *AGE*-variable was expressed in a natural logarithmic term. For MLR application, the regression functional $y(\mathbf{x}, \mathbf{w})$ in Eq. 1will be performed ina linear combination of the independent variables. Two linear regression equations associated with the two strength predicted approaches can be state as the following Eqs. 4–5:

For Model-A1:

$$UCS = y(\mathbf{x}, \boldsymbol{\beta}) = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 FA + \beta_4 W_s + \beta_5 W_b \tag{4}$$

For Model-A2:

$$UCS = y(\mathbf{x}, \boldsymbol{\beta}) = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 FA + \beta_4 W_s + \beta_5 W_b + \beta_6 UPV \tag{5}$$

where *A* denotes $ln(AGE)$; β_0, β_1, β_2,…,β_6, are the regression coefficients.

Artificial Neural Networks (ANN) for Regression

ANN is an alternative approach which is powerful to deal with class complex behavior problems of general regression due to its “learning” and “adapting” capacities.(Sazli, 2006; Aggarwal et al., 2013) In comparison with the classical regression analysis (linear or nonlinear), when ANN is applied, prior knowledge of functional relationship among variables is not required. ANN is a parallel distributed processing system, usually consisting of an input, an output layer, and one or more hidden layers, jointing together by neurons. It is reported that several types of ANN have been successfully developed over the last decades, and the multi-layered feed forward neural network, cascade forward neural

network, and radial basis function neural network (RBFNN) are especially useful and widely used for regression.(Wu et al., 2012; Yilmaz and Kaynar, 2011)

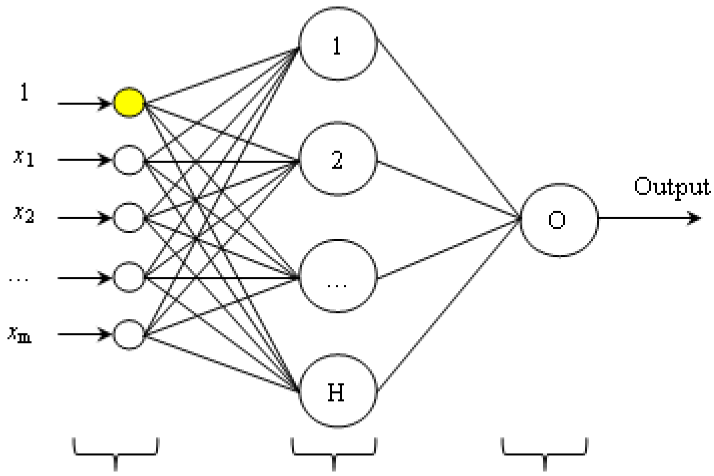

Figure 1: Typical Architecture of a Feed Forward Neural Network

FFNN with one hidden layer is typically illustrated in Figure 1. Outputs of each layer become inputs of next layer and there is no connection between neurons in the same layer. For ANN implementation, the functional regression is explicitly described as the following Eq. (6).

$$y(\mathbf{x},\mathbf{w}) = v\left[\sum_{h=1}^{H} w_{2h}.u\left(\sum_{j=1}^{m} w_{hj}^{(1)} x_j + w_{0h}^{(1)}\right) + w_0^{(2)}\right] \tag{6}$$

where, $x_j\ (j = 1,2,...,m)$ is the signal from the input layer; m is the number of inputs; *H* is the number of neurons in hidden layer; **w**is a matrix consisted of all weight and bias coefficients; $u(\cdot)$ and $v(\cdot)$ are the neuron activation (or transfer) functions in hidden and output neurons, respectively. In addition, the cascade forward network (CFNN) is similar to FFNN with the exception that it has a weight connection from input layer to each layer and from each layer to successive layers. The additional connections might improve the training speed in providing a desired input-output mapping.(Beale et al., 2012)The main difference in the CFNN is that each layer of neurons relates to all previous layers of neurons. (Goyal, 2011). A back propagation algorithm is the mostly used in training FFNN or CFNN that subsequently computes the derivatives backward through the network from the output to hidden and input nodes using the chain-rule of calculus.

Radial basis function network is another type of feed-forward ANN, frequently used for approximating function for a given input–output patterns.(Wu et al., 2012)Architecturally, a RBF network comprises of input, output layer and single hidden layer. The major difference between FFNN and RBFNN is located at neurons in hidden layer. Unlike FFNN that often uses sigmoid function (*S*-shaped), RBFNN commonly employs Gaussian radial basis function (bell-shaped) as activating function for hidden neurons.

Prediction Error Evaluation

The predictive capacity of the developed-regression models were monitored based on quantitative evaluation of some statistical indices including mean absolute percentage error (*MAPE*), root mean square error (*RMSE*), and coefficient

of determination (R^2). These parameters calculated as Eqs. 7–9 are examined on training and testing dataset. In the statistical viewpoint, the value of R^2beingclose1.0 and the value of *MAPE, RMSE* being as small as zero reflect a better prediction and vice versa.

Mean absolute percentage error (*MAPE*): $$MAPE(\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{t_i - y_i}{y_i}\right| \cdot 100 \quad (7)$$

Root mean square error (*RMSE*): $$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_i - y_i\right)^2} \quad (8)$$

The coefficient of determination (R^2): $$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(t_i - y_i\right)^2}{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)^2} \quad (9)$$

here t_i and y_i denote the actual and predicting value, respectively; $\bar{t}$ is the average value of the actual values; N is the number of data points.

ANALYSIS RESULTS AND DISCUSSIONS

Multiple Linear Regression Analysis

The Statistical Package for Social Sciences (SPSS) with the forward and enter technique was employed to provide regression models. Statistically, the "goodness" or fitting capacity of the developed regression models is mainly examined through following criteria: correlation coefficient (R), determination of coefficient (R^2), the F-test and the t-test. These statistical parameters calculating at the 95% confidence level for the three selected MLR models were summarized in Table 2.

The analysis of variance (ANOVA) was applied to evaluate the significance of the regression coefficients in the suggested models. It also meant that whether linear formula could be suitable to perform the relationship between dependent and independent variables. In this case, the F-test and t-test techniques in statistic are employed. First, a null hypothesis that none of the independent variables (**x**) is related to *UCS* is tested via ANOVA F-test. A small value of p-Sig (or t-Sig) represents a high level of statistical significant and vice versa. In the three MLR models (see Eqs. 4-5), since the calculated F-values for the whole regression are greater than the tabulated values at the level confidence of 95%, this null hypothesis is clearly rejected. In other words, there is a real linear-relationship between compressive strength and at least one of the considering variables. Second, significant test of all individual coefficients in the predicted models (ANOVA t-test) exhibits all calculated t-values associated to the corresponding variables are greater than the tabulated values at 95% confidence level (or the t-significant value is less than 0.05). The null hypothesis is also reasonably rejected at the confidence level nearly 100%. That is, it is also existed a real linear-correlation between all independent and dependent variables. In addition, it was found that the coefficients of correlation obtained from the proposed MLR models are fairly high (R^2 = 0.885 and 0.889), indicating a highly fitting capacity. In conclusion, to predict CLSM compressive strength from its mixture (Model-A1), the Eq. 4 is ready to use; and estimation of strength based on UPV (Model-A2), the Eq. 5 would be satisfactory. However, it was noteworthy that the estimation of one day-strength was much error or even negative (infeasible value), because the *AGE*-variable was deviated significantly from the linear regression equations ($ln(AGE)=0$).

Table 2: Result of Statistical Analysis for the Established MLR Models

Model	Input Variables	β_i	*t*	*t*-Sig.	*R*	R^2	*F*	*p*-Sig.
Model-A1 (Eq. 4)	Constant	-12.263	-4.551	0.000	0.941	0.885	121.671	0.000
	A	0.103	15.377	0.000				
	B	0.102	4.684	0.000				
	FA	-0.697	-10.950	0.000				
	W_s	-24.304	-4.103	0.000				
	W_b	2.160	4.243	0.000				
Model-A2 (Eq. 5)	Constant	-0.872	-12.227	0.000	0.948	0.898	176.602	0.000
	A	0.070	8.918	0.000				
	B	0.007	8.496	0.000				
	FA	-0.412	-5.754	0.000				
	UPV	0.672	6.670	0.000				

Proposed Multi-Layered Neural Networks

In this part, the ANN approach was employed to generate predicted strength functions, based on the Model-A1 and Model-A2. The input and output variables for ANN layouts are taken from the associated MLR formulas (MLR-I and MLR-II). The first ANN scheme simulating for Model-A1has five input neurons, representing for the curing age and four mixture parameters (*AGE*, *B*, *FA*, W_s, and W_b);and the later scheme has four input neurons, mapping to the UPV, testing age, and material contents in mixture (*UPV*, *AGE*, *B* and *FA*). Data obtaining from the laboratory test were used to configure ANN topologies for strength prediction. Randomly, 85input–output patterns extracting from 100 experimental database were employed for establishing models (70 patterns for training and 15 patterns for validating); and the remainders (15 data points)were considered as testing data to checking the generalized capacity. The Neural Network Toolbox in MATLAB was utilized for computation. Three types of ANN (FFNN, CFNN and RBFNN) consisting of one hidden layer were proposed to develop stable neural networks for strength prediction. For FFNN and CFNN, the hyperbolic tangent function (*tansig*) and linear (*pureline*) were used as transfer function in hidden and output neurons, respectively. It is widely agreed that interpolating capacity of an ANN model highly depends on the number of hidden layers and hidden neurons in each layer. These numbers must be enough to ensure generalization, meaning that the square error is minimized, along with the over-fitting prevention. The trial and error approach is often adopted to deal with this issue in deciding a suitable ANN topology.(Sadrmomtazi et al., 2013)For CFNN, the hidden layer was set to be the same as those of the trained FFNN, but the connecting weights from inputs to the output neuron are additionally added to the existing FFNNs. On the other hand, RBFNN have single hidden layer in which its hidden neuron number was determined during training work. In this process, one neuron was repetitively added to the single hidden layer at a time until the mean square error is below the threshold (approximate to the MSE in the trained FFNN) or the maximum number of neurons has been reached, whichever occurs first.

Table 3: Statistical Comparison of the Proposed Models

Model	Prediction Approach	Training Data			Testing Data		
		MAPE (%)	RMSE (Mpa)	R^2	MAPE (%)	RMSE (Mpa)	R^2
A1	MLR-I	28.317	0.108	0.885	20.451	0.093	0.912
	FFNN	3.585	0.015	0.997	11.088	0.055	0.976
	CFNN	4.852	0.020	0.995	9.668	0.046	0.981
	RBFNN	4.879	0.018	0.996	13.112	0.079	0.937

Table 2: Contd.,							
A2	MLR-II	23.414	0.090	0.898	25.318	0.110	0.878
	FFNN	7.366	0.042	0.978	12.731	0.052	0.973
	CFNN	7.265	0.044	0.977	14.559	0.056	0.976
	RBFNN	6.402	0.039	0.981	18.971	0.067	0.955

Table 3reports the result of correlation analysis for the obtained models including MLR and three kinds of ANN (FFNN, CFNN, and RBFNN). All regression models exhibit a potential prediction outcomes since high determination of coefficients values were achieved for MLR or ANN methods ($R^2 \geq 0.86$). Also, the ANN approach would be better than MLR in prediction because of higher R^2 and lower *MAPE* and *RMSM*. This result is logical because MLR is a linear-based approach, whereas ANNs is a combination of nonlinear functions. Thus, the trained ANN models become more flexible in description of input-output mappings. However, multivariable linear regression method is likely to use in practical applications owing to its advantages such as requiring no software, easy-to-use, and explicit regression formula.

CONCLUSIONS

In this paper, a potential usage of residual soil in producing CLSM as a backfill has been proposed. An experimental program was conducted with various mix proportion for investigation of its engineering properties, involving unconfined compressive strength and ultrasonic pulse velocity. In addition, we provided two models for prediction of compressive strength, called as Model-A1 and Model-A2. The Model-A1 interpolates UCS from the mixture proportion, whereas the Model-A2 evaluates UCS from UPV and several mixture parameters. Two methodologies were employed to build up the regression equations for the above two models: MLR and ANN. In MLR, two empirical linear formulas were built-up, according to Model-A1 and Model-A2. In ANN-based implementation, three types of neural networks (FFNN, CFNN and RBFNN) were simultaneously applied to develop stable ANN topologies for prediction in accordance with Model-A1and Model-A2. Analysis results show that compressive strength of the proposed CLSM can be well-predicted from its mixture constituents or the measured UPV by using MLR or ANN approaches. Moreover, the prediction of strength from ANN was significantly better than that of MLR, evidenced by comparing the several statistical parameters such as *RMSE*, *MAPE*, and R^2. Amongst the trained ANNs, the standard feed forward back propagation (FFNN) gives the best generality performance.

ACKNOWLEDGEMENTS

The author is grateful to Professor Yeong-Nain Sheen and Li-Jeng Huang (National Kaohsiung University of Applied Sciences, Taiwan) for his valuable comments on the first draft.

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